# Resource-Efficient Monitoring of Energy Storage Systems During Transport and Storage: A Data-Driven Approach to Early Short Circuit Detection

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Abstract: Due to national and international laws and regulations, the number of energy storage systems has risen sharply in recent years. While battery systems in operation can often be monitored by installed battery management systems to ensure safe operation, there are still no standardized monitoring methods for batteries during transport or storage. Consequently, this article proposes a solution for monitoring such batteries in the typical logistic processes of storage and transport. Particular attention is paid to a resource-efficient implementation of a data-driven algorithm that is adopted from existing literature and enables the early detection of internal short circuits, which are the main cause of thermal runaways of battery storage systems. As the transmission frequency of an external monitoring device is a particularly resource-critical variable, the extent to which different data frequencies influence the detection performance is also investigated.

## 1 INTRODUCTION

Energy storage systems (ESS) play a crucial role in energy transition initiatives worldwide. The main goal of this transition is to reduce energy consumption as well as greenhouse gas emissions but also to increase the utilization of renewable energy sources. In this regard, ESS enable the storage of renewable energy, which is often generated irregularly, therefore making electricity supply more sustainable and flexible. Two main application areas of ESS are in battery electric vehicles (BEVs) as well as battery energy storage systems (BESS) for residential and commercial applications. Their importance in the energy transition is clearly reflected in increasing sales figures over the last years. However, the use of ESS is always associated with logistical tasks such as transportation to the application or production site, the return at the end of life (EoL) for reuse or recycling as well as their storage at different stages of their lifecycle. During these periods, continuous monitoring of ESS is necessary due to the sensitivity of the integrated batteries, the resulting safety risks and for ongoing quality assurance. In this context, internal short circuits (ISCs) of battery cells in particular are a major source of danger. Research to date already offers promising artificial intelligence (AI)-based approaches that can recognize these short circuits. However, these require the constant availability of the battery management system (BMS), which is not reliably possible when transporting or storing ESS. In addition, the effect of reducing the monitoring frequency on the performance of these approaches has not been investigated. Against this background, we propose an approach, which can overcome this challenge thus enabling remote early battery short circuit detection for ESS in logistics scenarios.

The remainder of this paper is structured as follows: Section 2 outlines the research motivation, background, and challenges. Section 3 reviews related work. Section 4 describes the proposed solution. Section 5 presents experiments on inference frequencies for early short circuit detection, with results discussed in Section 6. Finally, Section 7 summarizes findings and suggests future research directions.



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## 2 BACKGROUND

ESS in BEVs as well as BESS in residential and commercial buildings are almost exclusively utilizing a lithium-based battery chemistry (IEA, 2022; Marsh, 2023). Under certain conditions, such as overcharging, overheating or mechanical damage, lithium-ion based batteries can catch fire or explode. This is due to the uncontrolled release of their energy in a short amount of time. This phenomenon is called thermal runaway and describes an uncontrolled and exponential increase in the temperature inside the battery, which may result in serious accidents. Following *Shahid and Agelin-Chaab (2022)*, the three major reasons for thermal runaway to start are mechanical (R1), electrical (R2) and temperature abuse (R3), all of which typically lead to an ISC. However, the speed at which an ISC can occur varies depending on the type of abuse and its severity (P. Sun et al., 2020). For this reason, early detection of an ISC is a particularly important aspect of battery safety and a vivid research topic.

Past research has already yielded a number of promising AI-based approaches that can detect ISCs at an early stage. However, these approaches expect the constant availability of the BMS. However, steady access to the BMS cannot be guaranteed away from their place of operation. This significantly increases the difficulty for safely handling ESS in logistics scenarios since the potential risk status of individual batteries cannot be reasonably monitored during pre- and after-sales processes by stakeholders such as logistics service providers or freight forwarders.

One possible approach to solve this problem is the use of an external device that can access the data from the BMS, while the underlying ESS is not in operation. Past research has already looked into the design and application of such a device, but focused solely on its utilization during the first life of an ESS at its place of operation. This work aims to bridge this gap, which has been acknowledged by current research projects (Plotnikov et al., 2023), and provide an approach that enables monitoring ESS in BEVs as well as BESS in residential and commercial buildings aside from their place of operation, especially during transportation and storage.

A key challenge when using an external device to record the BMS and environmental data of an ESS is its power supply. Especially in logistics scenarios, there are no fixed power sources. Moreover, additional framework conditions have to be observed when designing the external device and must be considered when solving the overall problem:

- **High energy usage for data transmission (FC1)** (Jayakumar et al., 2014)
- **High energy usage for complex computations (FC2)** (Tekin et al., 2023).
- **Continuous operational readiness (FC3)** (Callebaut et al., 2021)
- **Compact design and limited battery capacity (FC4)** (Callebaut et al., 2021; Jayakumar et al., 2014)
- **Longevity and low maintenance (FC5)** (Callebaut et al., 2021; Jayakumar et al., 2014).

In view of these conditions, it is necessary to develop an approach that balances the need for close monitoring with the limitations of the necessary battery operation.

Against this background, this work presents an approach that enables the collection of BMS data, namely voltage readings of all battery cells, and environmental data for ISC early detection using an external device to supplement an ESS during logistical processes such as transport and storage. Moreover, the main research question of this paper is: Is early ISC detection possible using a low monitoring data frequency? In order to answer this, a promising approach for early ISC detection from the literature (Schmid & Endisch, 2022; Schmid et al., 2022; Schmid, Kneidinger, & Endisch, 2021; Schmid, Liebhart, et al., 2021) is adopted and the results from respective research articles concerning the detection time for ISCs are validated in several experiments. In addition, the approach is compared to similar ones. Finally, the effect of the monitoring data frequency on the detection performance of the chosen approach is investigated.

## 3 STATE OF THE ART

Battery fault detection methods can be divided into three different classes: threshold based, model-based and data-driven methods (Schmid, Kneidinger, & Endisch, 2021; Shang et al., 2024). There are also different types of features that are used; some of them directly measurable, e.g. voltage and current, others not, e.g. state of charge (SoC) and capacity or state of health (SoH).

Threshold based methods follow the approach of defining a critical threshold for directly measurable features, which, when exceeded or undercut, indicate a fault. Model-based approaches attempt to estimate features that cannot be measured directly and then use them for error detection. The idea behind data-driven methods is to use techniques from mathematical statistics to derive regularities and patterns from battery data recorded during operation.

In the early stages of an ISC with relatively high short circuit resistance the effect on the aforementioned battery features is rather small ("soft" ISC) which makes it very difficult to detect the fault at this early stage by directly introducing critical threshold values (Lai et al., 2020; Schmid & Endisch, 2022). Thus, threshold-based approaches are hardly the correct tool for early ISC detection.

The review *Shang et al. (2024)* gives a thorough treatment of the most recent research literature concerning model-based and data-driven approaches. As noted in *Schmid et al. (2022)*, model-based approaches mostly suffer from the drawback that the reliability of feature estimations cannot really be secured. Therefore, the present work focuses on data driven methods.

In the literature many different data driven and machine learning approaches are described: Isolation Forest (Jiang et al., 2022), Support Vector Machines (Yao et al., 2021) various neural network architectures, for example LSTM and Radial Basis Function neural networks (Ojo et al., 2021; Wang et al., 2021) and Local Outlier Factors (Z. Sun et al., 2022) can all be found as employed detection methods.

A major challenge in the early detection of ISC is the robustness against noise in the sensor data (Schmid & Endisch, 2022; Schmid, Kneidinger, & Endisch, 2021; Shang et al., 2024). This makes Principal Component Analysis (PCA) a good detection approach.

One disadvantage of PCA is that the projection used for dimension reduction is purely linear, which means that non-linear structures in the data may be lost in the process. This makes PCA an unsuitable tool for non-linear variations data such as cell level voltage data of a battery in low SoC range (Schmid & Endisch, 2022; Schmid et al., 2022; Schmid, Liebhart, et al., 2021).

In *Schmid and Endisch (2022)*, *Schmid, Liebhart, et al. (2021)* and *Schmid et al. (2022)* the non-linearity problem is tackled by using a non-linear extension of PCA, the kernel PCA (KPCA) originally introduced in *Schölkopf et al. (1997)*. Solving both the non-linearity and the sensor noise issue makes the KPCA model from *Schmid and Endisch (2022)*, *Schmid, Liebhart, et al. (2021)* and *Schmid et al. (2022)* a very promising approach for early ISC detection in our use case scenario.

None of the aforementioned methods have been applied for lower data frequencies. Moreover, the review we conducted suggests that there is no research that addresses the issue of whether data frequency during the monitoring phase has any impact on ISC detection performance.

The scientific approaches to tracking systems developed to detect ISCs were also investigated. In this regard the authors of *González et al. (2022)* conducted a comprehensive literature review which did not find any previous works concerning tracking systems using IoT technology. In *Haldar et al. (2024)* a real time tracking system for the SoC and SoH of three-wheeled battery-operated vehicles is introduced. The external device used for data collection uses the batteries to be monitored as its power source. The collected data is sent to a cloud-based backend for processing. In *Gupta et al. (2020)* a similar approach is presented for monitoring batteries in BEVs with an external device that uses a battery power supply and transmits data regarding the SoC and SoH to a cloud backend.

However, all the reviewed approaches are developed for operation during the first-life use of the monitored batteries and at their place of operation. More importantly, early detection of short circuits is not carried out in any of the reviewed works.

# 4 SOLUTION PROPOSAL

In the following, we present our approach to monitor ESS in logistics scenarios such as transport and storage. The approach aims to address the challenges and framework conditions described in section 2. The central assumption when designing a solution for the given context is that BMS and environmental data can only be collected by an external device that has its own power supply in the form of a battery. The main goal of the approach is to enable continuous ISC early detection in ESS, especially in logistics scenarios. In this context, the FCs mentioned in section 2 lead to several requirements (REs):

- RE1 (derived from FC1, 4 and 5): The approach should be able to early-detect ISCs using only low frequency BMS data.
- RE2 (FC2): Computations should be offloaded from the external device as much as possible.
- RE3 (FC3): The approach should allow continuous monitoring.

Looking at the root causes for thermal runaway, it is assumed that any form of abuse of a battery leads to an increased risk of an ISC. The approach should reflect this, hence additional requirements can be derived:

- RE4: The approach should be able to detect mechanical (R1), electrical (R2) and thermal (R3) abuse.
- RE5: The approach should be able to change data collection frequency according to predefined conditions.

Looking at the requirements, RE 1 is most important for the feasibility of the proposed approach. Since the transmission of BMS data from the external device to a receiver has a high energy demand, the frequency at which the device sends its data to a receiver is a critical variable. This must be set as low as possible without impairing the monitoring of the ESS. This requirement also corresponds with the main research question of the present article, if early ISC detection is possible with low monitoring data frequency. In this context, the literature review suggests using a data driven AI detection approach. Against this background, a series of experiments are conducted in Section 5 to examine which approaches are suitable and what effects different data frequencies have on the performance of the selected approaches.

RE 2 is addressed in the presented approach by introducing 2 different layers for data processing:

- The edge layer that comprises the external device and enables the collection of BMS and environmental data.
- The cloud layer, which receives and processes the collected data from the edge layer.

In this context, we propose a variable data collection frequency in the edge layer, addressing RE3 and RE5. Under normal conditions, a baseline frequency minimizes power consumption from processor load and data transmission. However, external factors like movement, vibration, or temperature changes trigger an adaptive increase in detection frequency. This requires sensors to monitor environmental variables such as speed, rotational movement, and temperature. Rule-based logic enables the detection of potential abuse, addressing RE4.

The cloud layer is horizontally scalable for data ingestion, processing, and distribution, leveraging established IoT and big data technologies. Communication between the edge and cloud layer uses mobile standards (GSM, LTE, 5G) and lightweight protocols (e.g., MQTT, CoAP, AMQP). Data processing involves two components: model training and inference. To monitor batteries throughout their lifecycle, training data must capture normal behavior across the cycle. As lab data for new battery types may be limited, models require continuous retraining to improve predictions.

Inference occurs in real time to identify critical batteries promptly and notify stakeholders. Therefore, the approach employs a lambda architecture, with periodic training in the batch layer and real-time inference in the streaming layer. Example technologies to implement this are Apache Kafka[1], Hadoop[2], Apache Spark[3] or Apache Storm[4].

# 5 EXPERIMENTS

In order to evaluate the feasibility of our approach, a series of experiments were conducted to examine the performance of early detection approaches with reduced data frequencies. In this context, a real battery with 6 cells connected in series was artificially short-circuited in a laboratory environment. This was carried out with three different resistors as the short circuit resistor (10Ω, 1kΩ, 10kΩ). Moreover, several different data frequencies were implemented for the inference phase, i.e., the phase after the induction of the short circuit (c. f. section 5.2). Each experiment was started with an initial phase in which the properly functioning cells were cycled over a period of time to generate data for training the model. After this, an external short circuit (ESC) was induced for one of the cells by implementing a load resistor and the time required by the detection algorithm to detect the short circuit was measured. In this regard, an ESC was triggered instead of an ISC for reasons of practicability. Although the behavior of an ESC is not identical to that of an ISC, *Zhang et al. (2017)* nevertheless states that an ESC can mimic the early phase of an ISC.

In *Schmid and Endisch (2022)*, *Schmid et al. (2022)*, *Schmid, Kneidinger, and Endisch (2021) and Schmid, Liebhart, et al. (2021)* the principal idea for ISC detection is to look at relations between the single cell voltages of a system. As discussed in section 3, the mathematical method that forms the basis of *Schmid and Endisch (2022)*, *Schmid et al. (2022)*, *Schmid, Kneidinger, and Endisch (2021) and Schmid, Liebhart, et al. (2021)* is principal component analysis (PCA), which is optimized and exploited in many different ways to perfectly suit the problem. In

[1] https://kafka.apache.org/
[2] https://hadoop.apache.org/
[3] https://spark.apache.org/
[4] https://storm.apache.org/

particular in *Schmid and Endisch (2022)*, *Schmid, Liebhart, et al. (2021)* and *Schmid et al. (2022)* the authors utilize the non-linear extension kernel principal component analysis (KPCA) which makes it possible to address non-linear relationships in the data. The line of attack for fault detection is to check how close a given cell's voltages vector lies, after a transformation, to the principal component space that was computed using training data. More precisely the so called $T^2$- and Q-test statistics values of the vector of cell voltages are computed while monitoring. The general principle is that low $T^2$- and Q-values correspond to data which is similar to the training data while high values display anomalous behavior.

We compared the detection performance of the KPCA ($A_1$) approach with respect to short circuit detection time with all other approaches found in the scientific literature, which also only require the voltage values of individual battery cells for the detection. More precisely, plain PCA (Schmid, Kneidinger, & Endisch, 2021) ($A_2$) and a very simple method that just tracks the voltage difference between the cells (Lai et al., 2020) ($A_3$) were evaluated as well.

## 5.1 Experimental Setup

The batteries utilized in this study are Samsung INR18650-32E cells, each with a nominal capacity of 3.2Ah. These cells feature a lithium-nickel- cobalt-aluminum oxide cathode paired with a graphite anode. The cells have been arranged in a series configuration using 3D-printed cell holders. Individual monitoring of the cell voltage has been implemented using a Gantner Q.bloxx XL A107[5]. The cycling of the cells is managed using an EA-PSB 10080-120 power supply in conjunction with custom software tailored to administer the dynamic cycling protocol. To minimize the impact of external temperature fluctuations on short circuit detection, the entire experimental setup was housed within a thermal chamber maintained at 35°C.

## 5.2 Training

The detection algorithm was tested on ESC experiment datasets using 10Ω (R1), 1kΩ (R2), and 10kΩ (R3) resistors to induce short circuits. The 10kΩ resistor caused such a slow short circuit that the experiment was halted after several hours without detections, leading to the 10kΩ setting being discarded.

While the authors in *Schmid and Endisch (2022)* and *Schmid et al. (2022)* evaluated their approach with a fixed inference data frequency of 10Hz (Schmid & Endisch, 2022) resp. 0.1Hz (Schmid et al., 2022), in this work the detection time for all resistor values was evaluated for different inference data frequencies of 1Hz ($F_1$), $\frac{1}{60}$ Hz ($F_2$), $\frac{1}{300}$Hz ($F_3$), $\frac{1}{600}$Hz ($F_4$) and $\frac{1}{900}$Hz ($F_5$).

Since all approaches ($A_1$-$A_3$) were evaluated using the data sets from two different resistor settings ($R_1$ and $R_2$) while applying five different monitoring frequencies ($F_1$-$F_5$) 30 different experimental settings were studied.

To ensure the training dataset adequately represented the entire initial cycling phase without being overly large, 1000 evenly distributed points were selected. The data was first downsampled from 10Hz to 1Hz by averaging. Data points used for inference were excluded from the training set. For $R_1$ and $R_2$, the starting inference data point ($T_0$) was chosen about 30 minutes before inducing the short circuit.

The critical threshold for $T^2$- and Q-values in the KPCA approach was set at the 0.999-quantile of training data values. To address fluctuations in testing data, especially at higher monitoring frequencies, the detection logic required unusually high $T^2$- and Q-values to persist for 10 minutes. For the highest frequencies (1 Hz and $\frac{1}{60}$ Hz), the approach was further refined by requiring at least 20% of values in the last 10 minutes to be critical to detect a short circuit. For lower frequencies, this adjustment was unnecessary, as only one data point is transmitted every 5, 10, or 15 minutes.

## 5.3 Results

With the aforementioned detection logic implemented, the following detection times shown in Table 1 were achieved using the KPCA approach.

Table 1: Detection times of the KPCA approach using experimental settings $A_1R_{1,2}F_{1\text{-}5}$.

| | **1Hz** | $\frac{1}{60}$**Hz** | $\frac{1}{300}$**Hz** | $\frac{1}{600}$**Hz** | $\frac{1}{900}$**Hz** |
|---|---|---|---|---|---|
| **10Ω** | 2min 7sec | 1min | 6min | 1min | 1min |
| **1kΩ** | 151 min | 97 min | 133 min | 103 min | 253 min |

[5] https://www.gantner-instruments.com/de/produkte/bloxx/

The experiments were carried out again with the same detection logic for short circuit detection, but this time with PCA as the basis of the algorithm. In this context, identical detection times were observed for the 10Ω resistor (c. f. Table 2). However, the PCA approach did not work for the 1kΩ resistor. A short circuit could not be detected using any of the monitoring frequencies.

Table 2: Detection times of the PCA approach using experimental settings $A_2R_1F_{1\text{-}5}$.

| | **1Hz** | $\frac{1}{60}$**Hz** | $\frac{1}{300}$**Hz** | $\frac{1}{600}$**Hz** | $\frac{1}{900}$**Hz** |
|---|---|---|---|---|---|
| **10Ω** | 2min 7sec | 1min | 6min | 1min | 1min |

Finally, another approach was utilized in which a short circuit was considered to have been detected if the maximum difference between the individual cell voltages was greater than 0.5 volts (Lai et al., 2020). In this regard, the detection times for the 10Ω experiment were around 20 minutes for all frequencies. The approach did not detect anything for higher short circuit resistances.

## 6 DISCUSSION

Looking at the results of the conducted experiments, we conclude that the employed data driven methods can be utilized to enable early ISC detection with low monitoring frequencies. Specifically, the KPCA approach ($A_1$) yielded promising detection times compared to the other two approaches. Additionally, the results of detection times for the experimental settings $A_1R_{1,2}F_{1\text{-}5}$ are of the same order of magnitude as those in *Schmid and Endisch (2022)* and *Schmid et al. (2022)*, which supports the validity of our results regarding the detection times. The unsuitability of the PCA approach ($A_2$) for high short circuit resistances ($R_2$) has already been discussed in *Schmid et al. (2022)*. The voltage-difference approach ($A_3$) does not yield successful results for ($R_2$) either.

The results also show that there is no clear linear trend in the relationship between monitoring frequency and detection time in any of the experimental settings. This suggests that the detection times strongly depend on the distribution of selected data points, meaning they could vary with different data selections. In order to reinforce this assumption, the experimental settings $A_1R_{1,2}F_{1\text{-}5}$ were used again for detection with an initial time offset of $T_0$+7 minutes. The results show that detection times for lower frequencies (<= $\frac{1}{300}$Hz) increase up to 13 times, which further highlights that detection latency for low frequencies is highly influenced by the reception time of the data points.

Table 3: Detection times of the KPCA approach using experimental settings $A_1R_{1,2}F_{1\text{-}5}$ with $T_0$+7.

| | **1Hz** | $\frac{1}{60}$**Hz** | $\frac{1}{300}$**Hz** | $\frac{1}{600}$**Hz** | $\frac{1}{900}$**Hz** |
|---|---|---|---|---|---|
| **10Ω** | 2min 7sec | 1min | 8min | 8min | 13 min |
| **1kΩ** | 151 min | 97 min | 199 min | 79 min | 144 min |

Concerning the results of experimental settings $A_{1\text{-}2}R_{1,2}F_{1\text{-}5}$, we recognize that higher monitoring frequencies were not always faster in detecting ISCs compared to lower frequencies. This is in contrast to the naive expectation that a higher frequency enables faster detection. However, the detection logic seems to be a factor here - at higher frequencies, statistical value ($T^2$- and Q-values) fluctuations are more pronounced, whereas these fluctuations are less pronounced at lower frequencies. Therefore, the choice of a suitable detection logic is strongly frequency-dependent. In this study, a similar detection logic was used across all frequencies $F_{1\text{-}5}$ to enhance the comparability of the results. For practical applications, however, this means that different, frequency-optimized detection logics should be implemented.

In conclusion, our experiments show that using a data-driven approach such as KPCA is important to enable our solution proposal for low-frequency monitoring, energy-efficient, scalable battery monitoring. However, the precise settings of monitoring frequencies for different conditions must be determined for each battery type individually as the time from damage or abuse to thermal runaway depends on various factors, e.g. capacity (Zhao et al., 2016) or environmental influences (Ji et al., 2021). Therefore, the generalization from the conducted experiments to other battery configurations or real-world scenarios is not given and needs to be investigated in future research. Finally, the ISC early detection model must be trained anew for each different battery type.

## 7 CONCLUSION & OUTLOOK

This paper proposes a method for remote early detection of battery short circuits in ESS for logistics. It outlines the research background, motivation, and related work. While current ISC detection using BMS data works in controlled settings, it lacks support during transport and storage. Key requirements include low-frequency data collection to save battery life, cloud-based computation, and adaptive monitoring based on factors like temperature or movement.

The proposed solution involves a battery-powered external device for remote monitoring, collecting battery and environmental data, and a two-layer architecture: an edge layer for IoT-based data collection and a cloud layer for scalable analysis and real-time ISC alerts. The approach presented extends the state of the art by demonstrating a way of recognizing ISCs of ESS at an early stage in situations that were not previously considered in scientific literature.

In order to evaluate the approach, experiments with a 6-cell battery setup and artificially induced short circuits (10Ω, 1kΩ, 10kΩ resistors) to simulate early ISC phases were carried out. Voltage data was analyzed using KPCA for anomaly detection, which proved effective across different frequencies and outperformed both standard PCA and simpler voltage tracking methods.

Future research needs to investigate how analyzing data across the entire lifecycle of a battery could refine detection logic and improve accuracy. Moreover, the experiments should be carried out in more realistic environments and with different battery types so that the transferability of the approach can be evaluated. Finally, the computational costs of different detection approaches should be compared with each other.

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